Real-time capable neural network approximation of NUBEAM for use in the NSTX-U control system

M. D. Boyer[1]*, S. Kaye[1], D. Liu[2], K. Erickson[1], O. Meneghini[3], S. Sabbagh[4]

[1] *Princeton Plasma Physics Laboratory, Princeton NJ, USA*

[2] *University of California - Irvine, Irvine CA, USA*

[3] *General Atomics, San Diego CA, USA*

[4] *Columbia University, New York NY, USA*

Present-day and next step tokamaks will require precise control of plasma conditions, including the spatial distribution of rotation and current profiles, in order to optimize performance and avoid physics and operational constraints. The coupled nonlinear dynamics of equilibrium profiles and the complex effects of actuators on the equilibrium evolution motivates embedding physics-based and data-driven models within real-time control algorithms. Due to the important role of beam heating, current drive, and torque in establishing scenario performance and stability, a high-fidelity beam model suitable for use in real-time applications is desired. Motivated by the successful application of neural networks for rapidly calculating transport and pedestal pressure [1], this work describes a neural network that has been developed to enable rapid evaluation of the beam heating, torque, and current drive profiles based on measured equilibrium profiles. The training and testing database has been generated from the NUBEAM calculations output from interpretive TRANSP analysis of shots from the 2016 NSTX-U campaign [2, 3], augmented with scans of Z_{eff}, fast ion diffusivity, beam voltages, and beam modulation patterns. Neural network predictions made for the testing data demonstrate the ability of the model to generalize and accurately reproduce NUBEAM calculated profiles and scalar quantities. Results of processor-in-the-loop simulations of the model within the NSTX-U plasma control system demonstrate the suitability of the approach for real-time use and accelerated offline analysis.

Database development

The motivation for the neural network model developed in this work is to approximately reproduce the results of the NUBEAM code quickly enough to enable use in real-time control applications, between shots analysis, and scenario optimization on NSTX-U. To this end,

*This work was supported by the US Department of Energy Grant under contract number DE-AC02-09CH11466.

rather than attempting to create a model that accurately reproduces the entire predictive range of NUBEAM, which would require generating a comprehensive dataset encompassing the complete physically possible range of all of the inputs to NUBEAM, we focus on a subset of inputs with ranges defined by the operating space of the NSTX-U's first campaign in 2016. To generate the dataset, the interpretive TRANSP runs that are automatically run between NSTX-U shots were resubmitted with increased NUBEAM fidelity (5ms time steps and 10000 particles). Furthermore, for each shot, a grid scan was defined for key parameters, including Z_{eff}, edge neutral density, anomalous fast ion diffusivity, and beam voltages. Rather than submitting runs for all permutations of parameters, a subset of roughly 1000 runs based on approximately 250 shots was selected at random. The database includes nearly 100,000 time samples. Eighty percent of the shots in the dataset were randomly assigned to be used for model training, ten percent were assigned to validation, and the final ten percent were reserved for testing. No NUBEAM results from the discharges assigned to the testing dataset were used to train models, while validation data was used to assess accuracy and generalization during hyper parameter tuning. Inputs to the model were chosen to be beam powers, edge neutral density, Z_{eff}, electron temperature and density profiles, q profile, and fast ion diffusivity. The outputs to be predicted by the model were chosen to be the neutron rate, shine through, charge-exchange and orbit loss, and profiles of beam heating to ions/electrons, beam current drive and torque, and fast ion pressure.

Reduction of profile data and beam slowing down time effects

Radially varying quantities are represented in TRANSP on a discrete grid of points in the normalized toroidal flux coordinate ρ, typically using between 20 and 60 points. To reduce the number of inputs and outputs of the NN model, and therefore reduce the size of the datasets and time required for training and evaluation, the radially varying quantities were projected onto a set of basis functions. The basis functions for each quantity were chosen by applying principal component analysis of the dataset and keeping only the most significant modes, typically between 4 and 10. Figure 1 shows the number of modes required to explain 99.5% of the variance in the dataset for each profile compared to the number of modes kept in the model.

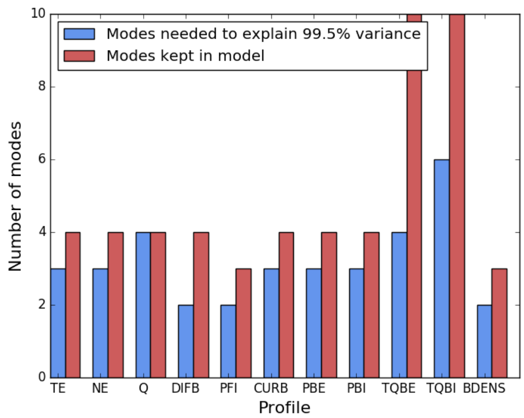

Figure 1: *Modes required to explain 99.5% of variance in dataset for each profile compared to the number of modes kept in the model reduction step.*

Due to the slowing down time of fast ions, the various effects of a beam on the plasma depend

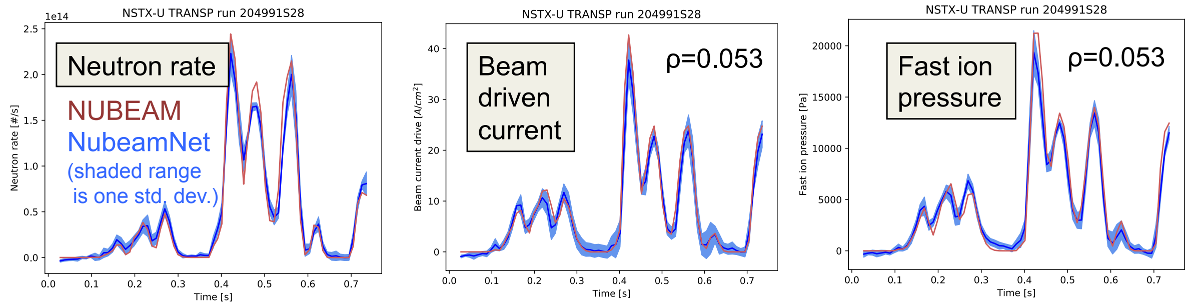

Figure 2: *Comparison of NubeamNet prediction to NUBEAM calculation for TRANSP run 204991S28: neutron rate (left), beam driven current at* $\rho = 0.053$ *(center), and fast ion pressure at* $\rho = 0.053$ *(right).*

on the time history of the discharge. Therefore, it cannot be expected that a model trained only on instantaneous values of the inputs should accurately predict the output behavior (unless the dataset is only made up of steady-state results). While many approaches could be taken to include time history effects in the model, including recurrent neural networks, the simple but evidently effective approach taken here is to augment the inputs of the model with a set of causal low-pass filtered versions of the individual beam powers. To account for the potential range of slowing-down times possible at different plasma conditions, the beam powers are filtered with time constants 0.02s, 0.05s, and 0.1s.

Model topology selection and testing results

A fully connected neural network topology was chosen for the models developed in this work. The choice of the number of hidden layers, hidden-layer nodes, and the regularization weight on the L_2-norm of the model coefficients was chosen through scoring how well models generalized to the shots in the validation dataset in a grid scan of hyperparameters. To provide improved estimates and a sense of the uncertainty of the estimated values, an ensemble of 5 models was trained, each on a randomly selected subset of the training dataset and all using the same neural-network topology. The output of the ensemble is taken to be the average output of the models, and the standard-deviation and range of the model predictions are used to provide estimates of the uncertainty of the predicted output.

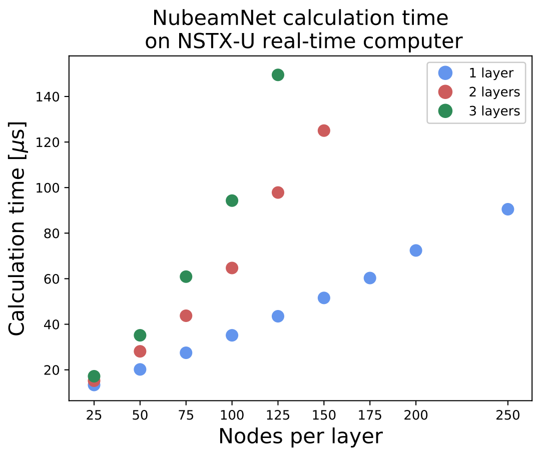

Figure 3: *Calculation time as a function of model complexity tested on the NSTX-U real-time control computer.*

Example comparisons of the NUBEAM calculation and NubeamNet estimation (with 3 layers of 125 nodes) for the neutron rate, the current drive at normalize toroidal flux $\hat{\rho} = 0.053$, and the fast ion pressure at $\hat{\rho} = 0.1$ are shown in Figure 2 for TRANSP run 204991S28. The results show that the neural network is able to closely approximate the time behavior.

The neural network was implemented in the NSTX-U real-time computer and a scan of model topology was conducted to assess the scaling of calculation time with model complexity. Results, shown in Figure 3, show that models with complexity near that required to optimize the model fit can be run within the typical 200μs cycle time of the NSTX-U control system. Recent advances in real-time PCIe-based internode communication in the NSTX-U control system [4] will enable offloading calculations to a dedicated computer with enough cores to simultaneously calculate the models for uncertainty quantification as well as calculation of the sensitivity of outputs to changes in inputs needed by real-time control and optimization algorithms.

Discussion

A neural network model for evaluating the beam heating, current drive, torque, and other effects of the NSTX-U neutral beam system on the plasma has been developed. The model was trained on NUBEAM results calculated for the discharges in the first NSTX-U campaign. The speed of the resulting model makes it well-suited for many real-time applications on NSTX-U, including equilibrium reconstruction and profile control [5, 6]. Future work will include developing training sets and models based on predicted discharges to make the model useful for planning future NSTX-U campaigns that are not within the operating range explored in the first campaign. Alternative approaches to handling the time-history dependence, including recurrent neural networks, will be also be explored.

References

[1] O. Meneghini, S. Smith, P. Snyder, *et al.*, "Self-consistent core-pedestal transport simulations with neural network accelerated models," *Nuclear Fusion*, vol. 57, no. 8, p. 086034, 2017.

[2] J. Menard, J. Allain, D. Battaglia, *et al.*, "Overview of NSTX Upgrade initial results and modelling highlights," *Nuclear Fusion*, vol. 57, no. 10, p. 102006, 2017.

[3] D. Battaglia, M. Boyer, S. Gerhardt, *et al.*, "Scenario development during commissioning operations on the National Spherical Torus Experiment Upgrade," *Nuclear Fusion*, vol. 58, no. 4, p. 046010, 2018.

[4] K. G. Erickson, M. D. Boyer, and D. Higgins, "NSTX-U advances in real-time deterministic PCIe-based internode communication," *Fusion Engineering and Design*, vol. 133, pp. 104 – 109, 2018.

[5] Z. O. Ilhan, W. P. Wehner, and E. Schuster, "Model predictive control with integral action for the rotational transform profile tracking in nstx-u," in *2016 IEEE Conference on Control Applications (CCA)*, pp. 623–628, Sept 2016.

[6] I. R. Goumiri, C. W. Rowley, S. A. Sabbagh, *et al.*, "Simultaneous feedback control of plasma rotation and stored energy on NSTX-U using neoclassical toroidal viscosity and neutral beam injection," *Physics of Plasmas*, vol. 24, no. 5, p. 056101, 2017.